Multispectral Remote Sensing and Site-Specific Agriculture: Examples of Current Technology and Future Possibilities*

E. M. Barnes
M.S. Moran
P.J. Pinter, Jr.
T. R. Clarke
USDA-ARS
US Water Conservation Laboratory
Phoenix, Arizona

ABSTRACT

Multispectral data can meet many of the information requirements of site-specific farming. Examples from the literature are presented where multispectral data has been applied to agricultural management problems. Some of the examples are illustrated using remotely sensed estimates of green leaf area index for a cotton field during the 1994 growing season.

INTRODUCTION

Remote sensing has shown potential for use in agricultural management for a number of years; however, the availability of fine spatial resolution, near real-time data has limited its application in the past (Jackson, 1984). New companies that provide aircraft-based imagery to meet the resolution and temporal requirements for agricultural management are now emerging. The promise of commercially available, high-resolution satellite imagery will also provide additional sources of remotely sensed data (Fritz, 1996).

Advances in precision farming technology (GIS, global positioning systems, and variable rate equipment) provide the tools needed to apply information from multispectral images to management problems. There is still considerable work to be done before the full benefits of remotely sensed data can be realized, but there are applications that can benefit from this data at the present time. The purpose of this paper is to provide an overview of how remotely sensed data can be utilized in site-specific agricultural management.

Vegetation Spectral Response

Digital imagery is obtained in distinct areas of the electromagnetic spectrum. Sensors used in vegetation monitoring are typically in the green, red, and near infrared portions of the spectrum. The importance of these spectral areas is illustrated by the high-resolution spectral response for a cotton canopy at different stages of development in Fig. 1. As the canopy develops, there is a definite increase in reflectance in the near-infrared

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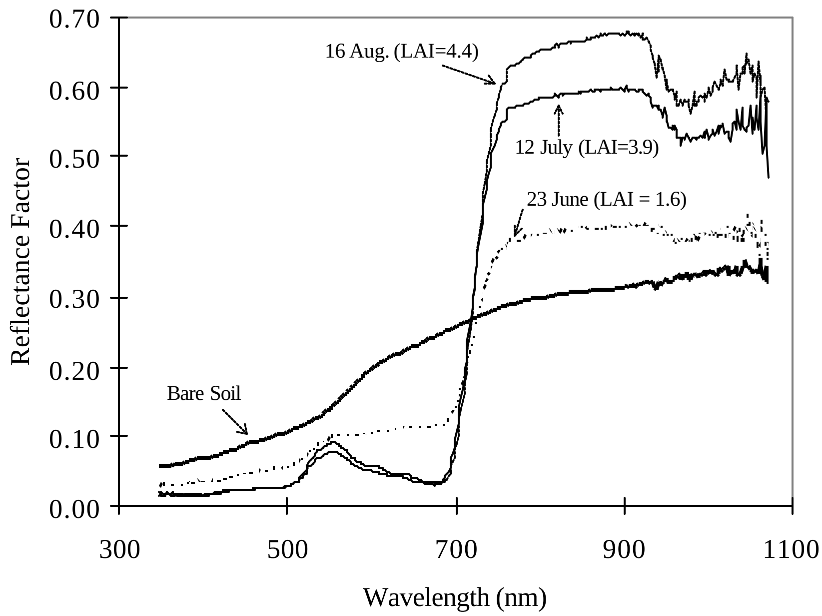

Fig. 1. High-resolution reflectance spectra for both a bare soil and a cotton canopy on different dates. Measurements of green leaf area index (LAI) are shown for the dates the spectra were acquired.

(~725 to 900 nm), as the internal leaf structure of the plant reflects more of the energy in this portion of the spectrum compared to a bare soil. There is also a development of a green peak (~ 550 nm) and decrease in red reflectance (~650 to 690 nm) due to chlorophyll reflectance and absorption respectively. Thermal imagery (8,000 to 12,000 nm) has also been proven useful in monitoring vegetation, as this imagery can be used to determine surface temperature. Any stress which lessens a crop's transpiration ability will result in a relative increase in the surface temperature of the leaves. Additional factors which impact the spectral response of crops to stress are presented by Jackson et al. (1986).

The spectral response of vegetation has been used to formulate several vegetation indices, such as the Soil Adjusted Vegetation Index (SAVI, Huete, 1988) expressed as

$$\mathrm{SAVI} = \frac{\mathrm{NIR} - \mathrm{RED}}{\mathrm{NIR} + \mathrm{RED} + \mathrm{L}}(1 + \mathrm{L}), \qquad (1)$$

where L is a dimensionless constant, and NIR and RED near-infrared and red reflectance, respectively. A good introduction to the interpretation of vegetation indices is provided by Jackson and Huete (1991), and the functional relationship between different indices is reviewed by Perry and Lautenschlager (1984). Vegetation indices are often well correlated with measures of plant density; as a crop's canopy develops, less bare soil is apparent, and thus a decrease occurs in red reflectance with an increase in NIR reflectance.

Previous Applications of Remote Sensing for Farm Management with Implications to Site-Specific Agricultural Management

Several methods have been developed to assess both soil and crop conditions using multispectral imagery. Some studies using remote sensing for soil properties, pest detection, and water stress are presented in the following sections.

Soil Properties

Soil physical properties such as organic matter have been correlated to specific spectral responses (Dalal and Henry, 1986; Shonk et al., 1991). Therefore, multispectral images have shown potential for the automated classification of soil mapping units (Leone et al., 1995). Such direct applications of remote sensing for soil mapping are limited because several other variables can impact soil reflectance such as tillage practices and moisture content. However, bare soil reflectance could have an indirect application in interpolating the results of gridded soil samples. For example, Fig. 2 shows a gray-scale image in the red portion of the spectrum. Percent sand and clay in the top 30 cm of the soil horizon is displayed over the approximate location of point samples taken by Post et al. (1988). Note that the brighter portions of the image correspond to areas of high sand content.

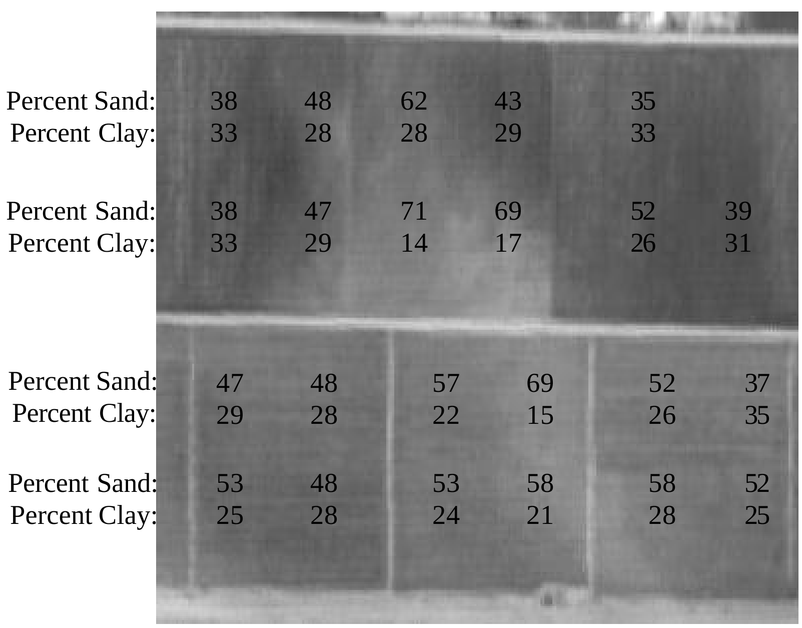

Fig. 2. Gray-scale image of a fallow field in the red portion of the spectrum with point measurements of percent sand and clay shown over the approximate sampling locations.

Vegetation spectral response has also been used to infer other soil conditions. Wiegand et al. (1994) showed a vegetation index was useful in mapping soil salinity over a sugar cane field. The nitrogen status of crops has also been estimated using remotely sensed data (Blackmer et al., 1995; Filella et al., 1995). Yang and Anderson (1996) describe methods to utilize multispectral images of vegetated fields for the determination of within-field management zones for application to site-specific farming.

Pest Detection

Sprayer mounted sensors have been found useful for the control of herbicide applications (such as Shearer and Jones, 1991). Brown and Steckler (1995) developed a method to use digitized color-infrared photographs to classify weeds in a no-till corn field. The classified data were placed in a GIS and a decision support system was then used to determine the appropriate herbicide and amount to apply. Penuelas et al. (1995) used reflectance measurements to assess mite effects on apple trees. Powdery mildew has also shown to be detectable with reflectance measurements in the visible portion of the spectrum (Lorenzen and Jensen, 1989). The ability to detect and map insect damage with remotely sensed imagery implies that methods can be developed to focus pesticide applications in the areas of fields most infected, thus decreasing the damage to beneficial insects.

Water Stress

The difference between remotely sensed surface temperature and ground-based measurement of air temperature has been established as a method to detect water stress in plants (Jackson et al., 1981). More recently, methods to integrate spectral vegetation indices with temperature have been used to improve remotely-sensed estimates of evapotranspiration (Carlson et al., 1995; Moran et al., 1994). Moran et al. (1994) defined a Water Deficit Index which uses the response of a vegetation index to account for partial canopy conditions, so that false indications of water stress due to high soil background temperatures were minimized. Spectral indices have also been used to determine "real-time" crop coefficients to improve irrigation scheduling (Bausch, 1995).

EXAMPLE DATA SET

Some of the capabilities of multispectral images are illustrated using a subset of data from the Multispectral Airborne Demonstration at Maricopa Agricultural Center (MADMAC) conducted during the summer growing season in Arizona (Moran et al, 1996). Images were acquired in four spectral bands (green, red, near-infrared and thermal) at a spatial resolution of 2 m, from April to October, 1994. The data presented here correspond to a field planted with two varieties of an upland cotton (Gossypium hirsutum L.) on April 5, 1994. The field was used in studies of irrigation efficiency by Watson (J.W. Watson, 1994, personal communication), and was divided into 12 irrigation borders. The irrigation levels and border layout are pictured in Fig. 3.

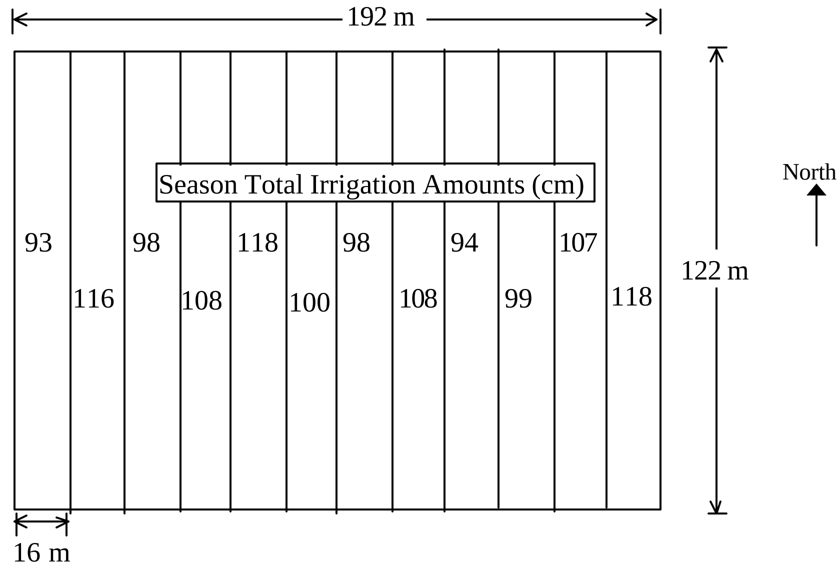

Fig. 3. Field layout and irrigation levels of a cotton field at Maricopa, AZ, in 1994.

The near-infrared and red images were calibrated to units of reflectance and then the SAVI was calculated. The SAVI was further modified to units of green leaf area index (LAI) using an empirically derived relationship (Moran, et al., 1996), where

$$LAI = -3.45 \ln(1 - SAVI) - 0.58. \qquad (2)$$

Gray-scale representations of the LAI over the cotton field for different dates in 1994 are pictured in Fig. 4. Darker shades of gray represent higher values of LAI. The maximum LAI was 4.9 and occurred in the August 2 image. The average field conditions for the dates shown in Fig. 4 are listed in Table 1.

The first point of interest in Fig. 4 is the center and lower right hand portion of the field that had a consistently lower LAI throughout the season. Similar patterns were visible in images from previous years. It is likely that this response was due to a higher sand content than that of the surrounding portions of the field, indicating precision applications of herbicide and fertilizers may be advantageous. The tendency of the southern portion of the field to have a lower LAI, especially early in the season, may be an indication of non-uniform irrigation applications or variation in soil type. The impact of the different irrigation levels on LAI was evident by August 2 (irrigation levels were essentially the same until July 9).

The images indicated LAI reached its maximum value for most of the field on August 2. Beginning August 16, LAI decreased, which is also the time white fly and leaf perforator damage was first observed in the field. The damage appeared to begin on the eastern side of the field and spread to the west as indicated by the more rapid decrease in LAI in the east for later dates (note that defoliant was not applied until September 9).

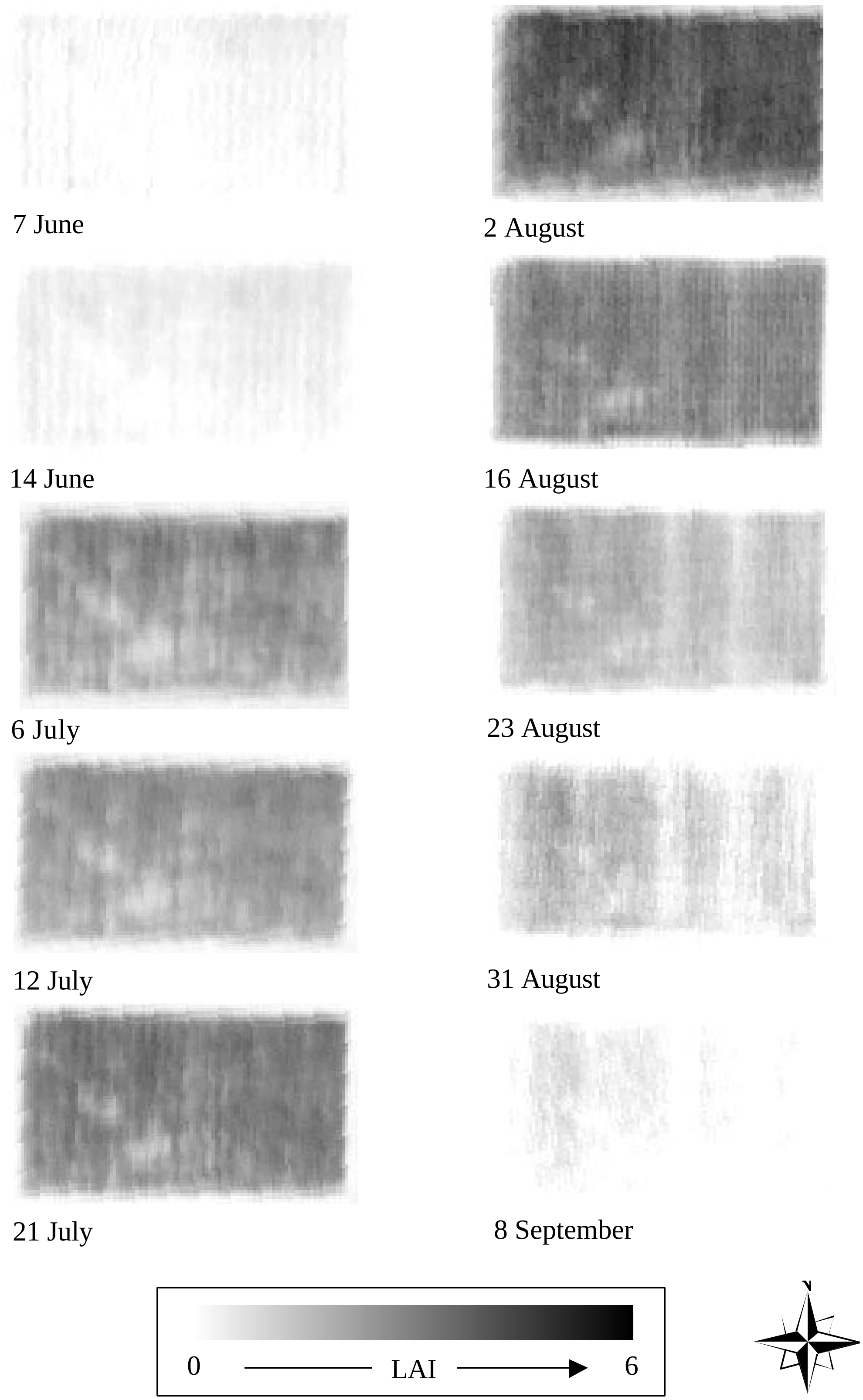

Fig. 4. Remotely sensed estimates of leaf area index (LAI) over the cotton field with the irrigation treatments shown in Fig. 3 for ten days during 1994.

Table 1. Average field conditions corresponding to the dates of each image in Fig. 4.

Date	Percent Cover	Average Height (cm)	Growth Stage
7 June	25	25	15-Leaf
14 June	30	30	Flowering
6 July	50	30	
12 July	80	50	
21 July	80	70	
2 August	95	85	
16 August	100	100	Mature Bolls
23 August	100	100	
31 August	100	100	
8 September	100	100	

From this example, it can be seen that multispectral images of red and NIR reflectance are useful for monitoring changes in vegetation patterns and development. It should be noted that the data presented in Fig. 4 were based on images calibrated to units of reflectance (that is, sensor characteristics and solar illumination conditions have been accounted for). Without this calibration, temporally-consistent estimates of LAI would not have been possible.

FUTURE POSSIBILITIES

Several applications have been developed to use remotely sensed data to infer both plant and soil characteristics. Three approaches of development appear to be emerging in the application of remote sensing and site-specific agriculture. In one approach, multispectral images are used for anomaly detection; however, anomaly detection does not provide quantitative recommendations that can be directly applied to precision farming. A second approach involves correlating variation in spectral response to specific variables such as soil properties or nitrogen deficiency. For example, in the case of nitrogen deficiency, once site-specific relationships have been developed, multispectral images can then be translated directly to maps of fertilizer application rates.

The third approach is converting multispectral data to quantitative units with physical meaning (such as LAI or temperature) and integrating this information into physically based growth models. For example, Moran et al. (1995) utilized remotely sensed estimates of LAI and evapotranspiration as inputs to a simple alfalfa growth model. The remotely sensed estimates were used to adjust the model's parameters throughout the season and resulted in improved predictions. Other applications of growth models with remotely sensed data are under development (Mougin et al., 1995; Carbone et al., 1996). Using remotely sensed inputs to growth models also provides a means to obtain predictions over large areas, which will increase the application of these models to site-specific agricultural management.

The latter two approaches have potential for incorporating remote sensing into decision support systems in a geographical information system environment (for example, Brown and Steckler, 1995). Further development will ultimately allow farm managers to make informed decisions about site-specific applications of farm materials.

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